Journal of
Theoretical and Applied Electronic Commerce Research

MDPI

Article

The Role of AI Technologies in E-Commerce Development: A European Comparative Study

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Abstract

As global economies accelerate their digital transformation, artificial intelligence (AI) technologies have become a key driver of innovation and economic growth, especially in the electronic commerce sector. This study examines the impact of AI applications in marketing and sales on e-commerce performance across European economies, using official data from Eurostat. Our methodology includes factor analysis to identify underlying data structures, linear regression to explore causal relationships, generalized linear model (GLM) multivariate analysis to assess the combined effect of multiple factors, and cluster analysis to categorize countries based on their level of digitalization. Our results demonstrate a strong correlation between AI use and e-commerce performance, revealing two distinct clusters with unique characteristics. The findings reveal a positive association between the use of AI and firms' engagement in e-commerce activities, although the influence on turnover appears more limited. This suggests that while AI facilitates entry into the digital marketplace, financial performance depends on a broader set of factors, including technological infrastructure, market readiness, and strategic alignment. These insights provide a solid basis for developing policies and strategies that support digital transformation and technological innovation in Europe, helping to build competitive and sustainable economies.

Keywords: artificial intelligence; e-commerce; digitalization; European Union

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Academic Editor: Peter O'Connor

Received: 4 June 2025

Revised: 12 August 2025

Accepted: 13 August 2025

Published: 1 September 2025

Citation: Bocean, C.G.; Popescu, L.; Simion, D.; Sperdea, N.M.; Puiu, C.; Marinescu, R.C.; Maria, E. The Role of AI Technologies in E-Commerce Development: A European Comparative Study. *J. Theor. Appl. Electron. Commer. Res.* **2025**, *20*, 225. https://doi.org/10.3390/jtaer20030225

1. Introduction

Over the past few decades, e-commerce has experienced a significant evolution, shifting from an emerging digital trade method to a central part of the global economy. This change represents more than just a technological advancement—it reflects a fundamental reorganization of consumer habits, business connections, and operational strategies. At the heart of this transformation is artificial intelligence (AI), which is no longer seen as a secondary tool but as a key driver of innovation, competitiveness, and sustainability in the digital era [1,2].

AI has become deeply embedded in the architecture of modern e-commerce, shaping every part of the value chain—from personalized interfaces and intelligent recommendations to logistics optimization, inventory management, and behavioral prediction. Using advanced machine learning algorithms, companies can analyze customer preferences in real-time, anticipate purchasing trends, and adjust their marketing strategies on the fly [3,4]. This situation reflects a significant redefinition of the relationship between consumers and technology, where AI acts as the unseen yet vital interface that mediates commercial interactions.

Within this framework, intelligent chatbots, personalized recommendation systems, predictive analytics platforms, and fuzzy logic engines have become common tools. They enable automated and adaptive decision-making processes that quickly respond to the complexity and volatility of market demand [5–7]. Furthermore, the integration of AI with emerging digital architectures, such as the Internet of Things (IoT), edge computing, and cloud technologies, further boosts the transformative potential of e-commerce ecosystems [8,9].

Europe, with its diverse and complex economic landscape, occupies a pivotal position in this transition. The speed and extent of AI adoption in e-commerce vary significantly across countries, reflecting differences in digitalization levels, the openness of the business sector to new technologies, investment in research and development, and the maturity of innovation policies [10,11]. While Northern and Western economies quickly adopt AI solutions into their digital commerce infrastructure, others progress more slowly, hindered by issues such as gaps in digital skills, unequal access to technology, and cultural reservations about automation [12,13].

This heterogeneity raises an essential question: to what extent does AI adoption impact the performance of the e-commerce sector in the European context? More specifically, is there a consistent relationship between the level of AI penetration in marketing and sales and the degree of enterprise involvement in e-commerce, as well as the revenue generated from these activities? Current studies offer partial answers, often limited to national perspectives or narrowly defined economic sectors. Without a solid comparative approach, there is a risk of applying local conclusions to a more complex European landscape, overlooking the differences rooted in each member state's economic, cultural, technological, and institutional specifics [14,15].

This paper aims to address a significant gap in the literature by examining how artificial intelligence (AI) technologies influence the development of e-commerce across European Union member states. The primary goal of the research is to analyze the relationship between AI integration—especially its application in marketing and sales—and measurable e-commerce outcomes at the national level. These outcomes are represented by indicators such as the percentage of enterprises engaged in online sales and the revenue they generate. The study does not attempt to isolate every operational or experiential effect of AI, such as efficiency or customer satisfaction, at the firm level; instead, it concentrates on observable economic patterns that manifest at the country level. The framework is based on the Resource-Based View (RBV), which treats AI as a strategic intangible resource capable of enhancing organizational competitiveness when supported by appropriate capabilities and infrastructure. Considering the systemic nature of digital transformation, this research emphasizes that AI's contribution must be evaluated within each nation's specific context, rather than as a universal technological solution.

To thoroughly evaluate AI's impact on e-commerce growth, the study employs four key variables that measure both technological adoption and economic outcomes. Data for each variable were collected from Eurostat, ensuring consistency and comparability across EU member states. The first two variables (percentage of businesses with e-commerce sales and percentage of total revenue from e-commerce) serve as primary indicators of e-commerce activity and performance, respectively. These metrics provide insight into the level of digital commercial activity at the national level.

The third variable, percentage of enterprises using AI technologies in marketing or sales, captures the degree of AI integration in firms' customer-facing operations. This indicator is central to understanding how technological sophistication translates into commercial behavior and outcomes. The fourth variable, percentage of ICT specialists in total employment, reflects the availability of technical human capital, which underpins a country's capacity to adopt and sustain digital innovation.

Despite the growing body of academic research on artificial intelligence in e-commerce, several limitations remain. Most current studies concentrate on single-country contexts or specific sectors, neglecting the variations in digital maturity across Europe. Furthermore, while many analyses highlight the benefits of AI in marketing and customer engagement, they often lack comparative assessments that link these technologies to important economic performance indicators, such as e-commerce penetration and revenue. The narrow focus of existing research creates a gap in understanding how different levels of AI adoption impact broader digital commerce outcomes in various national contexts. This study seeks to fill this gap by offering a cross-country comparative perspective, providing a more comprehensive and policy-relevant view of AI's role in driving e-commerce growth within the European Union.

The novelty of this study lies in its application of the Resource-Based View (RBV) framework to examine how AI, as a strategic digital resource, affects national e-commerce outcomes across European countries. Instead of focusing solely on technology adoption, the research assesses the performance-enhancing effects of AI through a cross-country analysis, employing a multi-method approach (factor analysis, GLM, regression, and clustering) based on official Eurostat indicators. This macro-level perspective broadens RBV applications beyond individual firms, providing new empirical evidence on how intangible digital resources influence economic competitiveness in the digital commerce ecosystem. Unlike previous research, which mainly concentrates on firm-specific or sectoral case studies, this study offers a comparative analysis that highlights how structural differences among countries affect the relationship between AI adoption and e-commerce performance.

The paper is divided into six sections. The introduction outlines the overall framework and motivation behind the research. The literature review explains the theoretical foundations. Section 3 details the research design. Section 4 presents the main empirical findings. The discussion interprets these findings concerning the existing literature, and the conclusion summarizes the paper's contributions and limitations, while suggesting future research directions.

2. Literature Review and Hypotheses Development

2.1. The Impact of Artificial Intelligence on the Development of E-Commerce

E-commerce has experienced a significant transformation over recent decades, becoming a key part of the digital economy. This shift has been driven by technological progress, globalization, and changing consumer behaviors, prompting organizations to adopt innovative solutions to remain competitive in a rapidly evolving market [16,17]. Among these innovations, artificial intelligence (AI) has emerged as a powerful force, transforming the way businesses operate online. As Russell and Norvig [1] state, AI is not just a technical tool but a strategic enabler that redefines company–client relationships, improves operations, and creates personalized experiences.

The conceptual origins of AI date back to the 1950s, marked by pioneering work on artificial neurons by McCulloch and Pitts, as well as Alan Turing's proposal of a machine intelligence test [18,19]. Since then, the field has progressed from theoretical models to practical applications, such as voice recognition systems and machine learning algorithms, which now support modern e-commerce platforms [20]. The rise of generative AI after 2020 further expanded these applications, allowing for the creation of content, images, and even code, thereby opening new commercial opportunities [21].

In today's e-commerce landscape, AI plays a versatile role by enhancing logistics, personalizing customer interactions, and improving inventory management [22]. Advanced algorithms allow platforms to analyze user behavior and generate personalized recommendations based on individual preferences and purchase histories [4,15]. Predictive analytics tools, for example, help forecast consumer demand, reducing the risks of overstocking or stockouts [14,23]. AI-powered chatbots also provide continuous customer support, quickly addressing inquiries and increasing satisfaction [24,25].

AI's influence extends deeply into marketing, offering substantial benefits. Sentiment analysis and natural language processing enable companies to monitor customer feedback in real-time and adjust their strategies accordingly [26,27]. AI-powered tools, such as recommendation systems, enhance conversion rates and drive revenue growth [27–29]. Davenport and Ronanki [30] found that platforms utilizing hyper-personalization through AI experienced up to a 30% increase in sales compared to traditional methods. These findings align with research by Salah and Ayyash [31], which highlights the positive impact of integrating AI into digital marketing strategies.

However, adopting AI introduces several challenges. Ethical issues related to algorithmic transparency, data privacy, and job disruption continue to ignite debate [13,32]. For example, the "black-box" nature of certain AI systems makes decision interpretation difficult, potentially undermining consumer trust [33,34]. Additionally, the high financial and human resource costs associated with AI implementation pose barriers for small and medium-sized enterprises (SMEs), which often lack the necessary infrastructure to adopt these technologies [11,13]. These points are consistent with the findings of Bawack et al. [35] and Rahayu and Day [10], who highlight regional differences in digital technology adoption.

The shift from Industry 4.0 to Industry 5.0 highlights another key aspect of this transformation, focusing on human–machine collaboration and sustainability [36,37]. In this setting, AI and the Internet of Things (IoT) form the technological foundation of modern e-commerce, enabling real-time data processing and enhanced supply chain management [8,38]. Vertical IoT models, which combine data processing layers from the edge to the cloud, enable companies to monitor information flows and predict market changes [9,39]. These developments support research by Milić and Babić [40] and Senyo et al. [41], who emphasize the vital role of cloud computing in digital transformation.

Across Europe, the adoption of AI in e-commerce varies significantly, influenced by factors like digital infrastructure, data protection laws, and consumer trust levels [42,43]. While Nordic countries have quickly adopted AI tools, such as chatbots and recommendation engines [44], Eastern European regions still face technological and workforce challenges [10,45]. These regional differences are further highlighted by studies from Bhatia and Thakur [46] and Leonard [47], which examine how organizational factors affect digital technology adoption.

Another notable development is the use of fuzzy logic in e-commerce. This approach improves operational accuracy by enhancing decision-making under uncertainty [7]. Additionally, the integration of advanced natural language processing into chatbots and virtual assistants is transforming customer engagement and increasing operational efficiency [48,49]. These technological advancements align with the findings of Batra et al. [50] and Huang et al. [51], which examine the role of automated negotiation agents in e-commerce.

AI continues to demonstrate promise in marketing by transforming promotional strategies and improving customer interactions [52]. AI-driven sentiment analysis helps businesses better understand customer reactions and tailor their messages accordingly [53]. Personalized recommendation systems also increase sales and strengthen customer loyalty [54,55].

The idea that using AI positively influences the proportion of companies selling online, as well as their revenues, is consistently supported by the academic literature (H1). In addition to streamlining processes [56], AI technologies generate new growth opportunities [2,57]. However, to achieve long-term success, businesses must address both ethical and technical challenges, balancing responsible innovation with operational efficiency [58,59].

Hypothesis H1. *The use of AI in e-commerce positively affects the proportion of businesses selling online and the overall sector turnover*.

2.2. The Relationship Between Adopting AI Technologies in Marketing and Sales and E-Commerce Performance Across the United States

The global economy is experiencing significant changes driven by digitalization, globalization, and shifts in consumer behavior—forces that have fundamentally altered how goods and services are produced, distributed, and consumed. E-commerce, which involves a range of commercial activities conducted via the Internet, has become one of the most visible signs of this evolution [16,17,47]. AI has played a catalytic role as the Internet has become an essential part of company operations, enabling the redefinition of business models, processes, and strategies within the realm of e-commerce [1,20,42].

The academic literature consistently highlights the many benefits that AI provides to e-commerce businesses. Some of the most important include personalized customer experiences, process automation, predictive analytics, and improved operational efficiency [2,4,56,57]. Branda et al. [3] emphasize that AI utilizes machine learning algorithms to analyze online consumer behavior and generate highly personalized product recommendations, which increase conversion rates and enhance customer satisfaction.

AI also plays a vital role in predicting demand and managing inventories more effectively, directly affecting operational sustainability [14,60]. In this context, AI-powered applications, such as conversational chatbots, have become standard on e-commerce platforms, offering 24/7 support and reducing the workload for human staff [34,61]. These tools not only increase efficiency but also build customer loyalty through smooth and continuous communication [24].

The integration of AI in e-commerce is accelerating due to advances in digital infrastructure, particularly through its convergence with the Internet of Things (IoT), edge computing, and cloud computing. This technological layering enables real-time data processing [8,9,41]. The vertical IoT model proposed by Lazić et al. [8] supports the integration of various AI techniques—such as convolutional neural networks (CNNs), reinforcement learning (RL), and fuzzy logic—based on the type of commercial relationships (B2C, C2C, C2B), allowing for unprecedented levels of customization in commercial strategy.

As AI becomes more integrated into business strategies, scholars have noted a positive correlation between a country's level of digitalization and the widespread use of e-commerce [10,11,45]. Countries that heavily utilize AI technologies in marketing and sales tend to have more companies involved in e-commerce and generate higher revenues in this sector [15,28,31]. These findings support the formulation of the second hypothesis in the present study, which investigates the potential causal link between advanced technology adoption and e-commerce success.

The use of AI in marketing has attracted significant academic interest over the past twenty years. Davenport et al. [26] and Kitchens et al. [27] highlight how sentiment analysis, hyper-personalized advertising campaigns, and real-time updates to communication strategies have changed the dynamics of the customer–supplier relationship. Madanchian [34] notes that AI significantly enhances sales by automating data analysis and facilitating informed decisions in pricing and trend detection. A particularly innovative feature is the use of fuzzy logic and neural networks to model decision-making uncertainties, enabling companies to operate effectively even during unstable economic periods [7]. Furthermore, applying natural language processing (NLP) in customer interactions improves communication and enhances the quality of support provided [48].

Despite these benefits, research also highlights several risks and challenges. These include the potential for job displacement, algorithmic opacity, and concerns about data privacy [13,32,33]. As demand for accountability and trust in automated systems grows, the concept of Explainable Artificial Intelligence (XAI) has become increasingly important in e-commerce [33,34]. Empirical studies demonstrate that companies utilizing AI not only enhance their operations but also achieve sustainable, long-term competitive advantages [3,4,31]. However, due to a shortage of skilled workers and technological obstacles, the adoption of AI in small and medium-sized enterprises (SMEs) remains inconsistent [11,12,47]. Rahayu and Day [10] emphasize the crucial role of public policy in fostering digital adoption, which has a significant impact on e-commerce performance.

Recent research also shows that the level of AI use varies across industries and regions, which in turn influences how quickly e-commerce spreads. In terms of active businesses and transaction volumes, e-commerce activity is higher in countries that make substantial investments in digital infrastructure and AI training [14].

By integrating AI with other advanced technologies like blockchain and augmented reality, e-commerce platforms can handle more tasks, especially in areas such as data security and personalized experiences [5,62]. In fashion e-commerce, for instance, AI applications allow for outfit personalization based on customer body shape, trend forecasting, and dynamic pricing [63,64].

The scholarly literature [2,14,26,32,34] offers a strong basis for articulating the study's second hypothesis:

Hypothesis H2. *Countries that use artificial intelligence technologies in marketing and sales (AIMS) more extensively tend to have a higher proportion of enterprises involved in e-commerce (ECOMM_PE) and report greater revenue from e-commerce activities. This indicates a link between the level of economic digitalization and the adoption of advanced technologies.*

This correlation indicates that investments in digitalization and AI can serve as catalysts for sustainable growth in e-commerce across Europe. However, a balanced approach is crucial—one that considers ethical concerns and ensures the development of suitable regulatory frameworks.

3. Materials and Methods

3.1. Research Design

This study employs a quantitative research design to explore the effect of artificial intelligence (AI) technologies on e-commerce performance in marketing and sales. Using secondary data from Eurostat, the research seeks to identify significant patterns and correlations between the level of digitalization in European economies and the adoption of advanced technologies. By examining the connection between digital integration and business success, the study provides a comprehensive view of how AI impacts online business practices.

The analysis centers on four key variables that measure both the level of e-commerce activity and how much businesses incorporate AI into their marketing and sales processes.

These variables were chosen to reflect not only the economic aspect of digital trade but also the pace of technological innovation across EU member states. The study employs four main statistical techniques—factor analysis, linear regression, multivariate general linear model (GLM), and cluster analysis—each selected to enable a thorough and multidimensional analysis of the data. These methods go beyond just describing relationships; they reveal underlying structures, test causal links, and group countries based on their digital maturity.

Although much of the existing literature on artificial intelligence and e-commerce tends to focus on the firm level, this study adopts a country-level perspective, aiming to understand how national structural conditions shape the path of digital transformation across the European Union. This choice is deliberate, based on both the nature of the research questions and the realities of data availability and policy relevance. Most initiatives related to digital infrastructure, AI adoption, and educational reforms are launched and managed at the national or supranational level, making the country a relevant unit of analysis when examining system-wide changes.

The variables used in this study are obtained from Eurostat, a trusted and standardized source of macro-level indicators. They represent aspects such as the percentage of companies utilizing AI in marketing and sales, the share of businesses engaged in e-commerce, revenue generated from online activities, the presence of ICT specialists within the workforce, and the overall quality of digital infrastructure. While firm-level data would provide more detail, such information is often incomplete or reported inconsistently across EU member states. In contrast, national-level data ensure comparability and analytical consistency.

Furthermore, many of the forces that influence the adoption and performance of AI technologies, such as digital maturity, institutional readiness, and policy coherence, are inherently systemic. These factors extend beyond individual organizations and operate at the societal level, affecting not only specific outcomes but also a country's overall ability to integrate technological innovation into its economy. From this perspective, a country-level approach helps identify significant differences and groups, emphasizing both digital divides and potential best practices across the EU.

Therefore, while this study does not dismiss the importance of micro-level inquiry, it serves as a complementary contribution by offering a comprehensive view of how structural, technological, and institutional factors work together to shape the development of AI-powered e-commerce across a continent.

The study's findings aim to be relevant not only to scholars but also to policymakers and practitioners seeking to understand or guide the digital transformation of Europe's economy. Ultimately, the research design combines statistical rigor with a practical approach, offering nuanced insights into how advanced technologies are transforming the e-commerce landscape. Figure 1 illustrates the conceptual model guiding this investigation.

The theoretical foundation of this study is based on the RBV theory, which claims that sustainable competitive advantage comes from effectively utilizing internal resources that are valuable, rare, inimitable, and organizationally embedded [6]. In this context, artificial intelligence (AI) is not an external novelty but a strategic resource that can enhance e-commerce performance when applied to marketing and sales processes. From an RBV perspective, AI technologies such as predictive analytics, recommendation systems, and intelligent chatbots are intangible assets that enable firms to optimize consumer targeting, personalize the customer experience, and enhance operational efficiency. When integrated into a robust digital infrastructure, these tools enhance a firm's ability to create value and differentiate itself in competitive online markets.

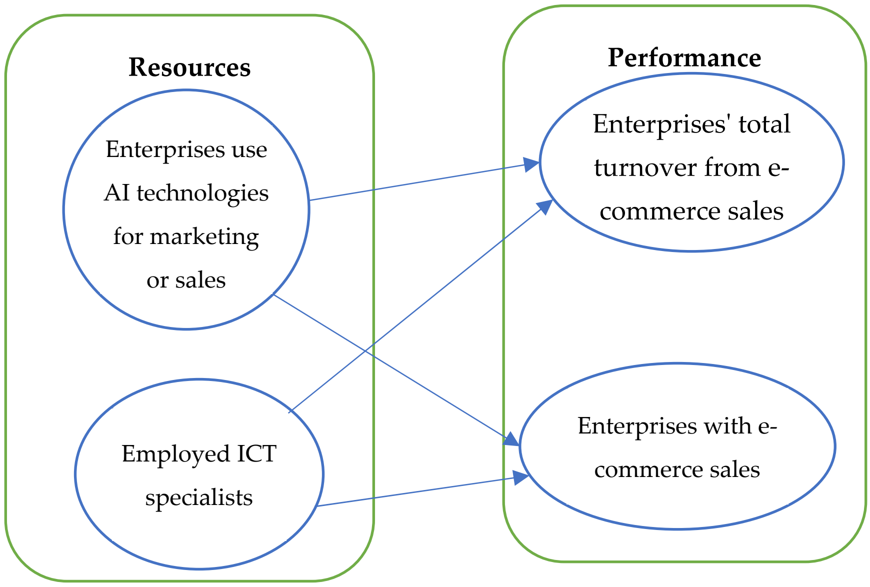

Figure 1. Conceptual model. Source: developed by the authors.

While the RBV theory has traditionally been applied at the firm level, several scholars have extended its logic to macroeconomic or national contexts, especially when analyzing the systemic capacity to deploy strategic resources such as digital technologies. For instance, Chen et al. [6] and Rahayu and Day [10] explored how structural capabilities at the national or industry level—such as ICT infrastructure, digital workforce availability, and regulatory support—can collectively influence technological outcomes across firms. These systemic enablers are not attributes of individual enterprises but are embedded within national ecosystems, which aligns with the RBV logic of resource orchestration and dynamic capability building.

This study extends the RBV framework to national-level analysis by treating AI not only as a resource held by individual firms but as a strategic digital asset whose effective deployment is influenced by institutional, infrastructural, and policy-driven factors. In this sense, AI adoption in marketing and sales (AIMS), when aggregated across sectors and measured at the national level, becomes a reflection of a country's capacity to embed intangible digital capabilities into its commercial fabric. This approach is consistent with macro-RBV extensions [5,35], which argue that intangible resources such as data infrastructure, knowledge capital, and AI capabilities can be studied at higher levels of aggregation when supported by robust institutions and policies.

Furthermore, there is growing precedent in the literature for conducting country-level analyses of digital transformation using firm-derived indicators. Studies such as OECD [11], Ozturk [14], and Aljarboa [12] demonstrate that aggregated metrics like percentage of firms using AI or employing ICT specialists can serve as valid proxies for national digital readiness and innovation performance. Our research aligns with this approach by combining Eurostat data, collected at the enterprise level but representative at the national scale, with advanced statistical techniques to examine structural differences across European economies.

3.2. Selected Variables

To capture the relationship between AI and the performance of the e-commerce sector across European Union member states, we employ four key variables that reflect both technological integration and economic outcomes. All indicators are sourced from Eurostat, the official statistical office of the European Union, ensuring consistency, comparability, and methodological transparency across countries. The variables are operationalized using harmonized instruments applied at the enterprise level and reported at the national level, making them suitable for macro-level analysis.

The first variable, ECOMM_PT (enterprises' total turnover from e-commerce sales), measures the percentage of total business revenue generated through online sales. This indicator captures the financial impact of digital commerce and reflects the economic success of firms in transitioning to digital markets. It serves as a proxy for e-commerce performance, enabling cross-country comparisons of digital trade intensity. The data are derived from Eurostat's survey module on e-commerce and reflect the self-reported share of turnover from digital sales channels.

The second variable, ECOMM_PE (enterprises with e-commerce sales), denotes the percentage of enterprises within each country that report conducting sales over the Internet. This variable is a measure of digital adoption and market penetration, indicating the extent to which firms are open to modern business practices and the use of online channels. It reflects structural engagement with e-commerce across sectors and is commonly used in benchmarking national progress toward digital transformation.

The third variable, EICTC (employed ICT specialists), measures the share of information and communication technology (ICT) specialists in the total workforce. It serves as a proxy for a country's capacity to adopt, maintain, and develop digital technologies, including AI-based systems. A higher percentage indicates a more developed digital labor market and stronger systemic readiness for technological innovation. This variable aligns with prior studies [11] that link human capital availability to digital competitiveness and innovation diffusion.

The fourth and central variable, AIMS, represents the percentage of enterprises using artificial intelligence technologies specifically for marketing or sales purposes. This construct reflects the strategic integration of AI tools in customer-facing business functions, including but not limited to recommendation engines, dynamic pricing systems, predictive analytics, sentiment analysis, and AI-driven chatbots. The variable is based on Eurostat's ISOC_EB_AI indicator, which aggregates firm-level responses to questions about AI deployment in commercial processes.

Although these variables are expressed as percentages, they capture multidimensional aspects of digital transformation. ECOMM_PT and ECOMM_PE measure economic output and market participation, respectively; EICTC reflects technical labor capacity; and AIMS captures the degree of strategic AI integration in marketing and sales. Together, these variables offer a composite picture of national digital maturity and innovation capability.

Importantly, the operationalization of AIMS is consistent with the theoretical framework adopted in this study, the RBV theory. From this perspective, AI functions as a strategic intangible resource that can enhance competitiveness when embedded into organizational routines. When examined at the macro level, the diffusion of AI in marketing and sales reflects a country's collective ability to mobilize digital resources to improve commercial performance. While we recognize that the AIMS indicator does not capture the depth or sophistication of AI use, its cross-national consistency, empirical relevance, and conceptual alignment with the RBV make it a suitable proxy for macro-level analysis.

All variables are expressed as percentages, which makes cross-country comparisons and detailed statistical analysis easier, as shown in Table 1.

All data used in this study were accessed through Eurostat's Data Browser and downloaded in tabular format. The variables were pre-processed and harmonized using Excel and SPSS. In addition, the data span multiple years (primarily 2021–2024) to account for variations in reporting timelines across countries and to ensure analytical robustness. When yearly data gaps were identified, we used the most recent available value for each country. This multi-year approach improves the reliability of findings and allows for a more comprehensive examination of digital transformation across the European Union.

Table 1. Research variables.

Variable	Dataset	Measures	References
ECOMM_PT	Enterprises' total turnover from e-commerce sales	Percentage of turnover	[65]
ECOMM_PE	Enterprises with e-commerce sales	Percentage of enterprises	[66]
EICTC	Employed ICT specialists	Percentage of total employment	[67]
AIMS	Enterprises use AI technologies for marketing or sales	Percentage of enterprises	[68]

Source: developed by the authors based on data collected from Eurostat [65–68].

3.3. Methods

To explore the relationships among variables and evaluate the proposed hypotheses, the study employs four primary statistical techniques. Factor analysis functions as a tool to uncover underlying structures within the data and simplify complexity by grouping variables into common factors [69]. This method relies on the correlation matrix and extracts components that explain most of the observed variance. The basic formula for factor analysis is as follows (1):

$$X = LF + \in \tag{1}$$

X—observed variables;
L—matrix of factor loadings;
F—latent factors;
$\in$—errors.

The Kaiser–Meyer–Olkin (KMO) test and Bartlett's test confirmed the dataset's adequacy for this analysis.

To assess the relationship between AI adoption (AIMS) and e-commerce performance (ECOMM_PT and ECOMM_PE), a linear regression analysis was conducted. The regression model takes the following Form (2):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \in \tag{2}$$

Y—dependent variable;
$X_1, X_2, \ldots, X_n$—independent variables;
β_0—intercept;
$\beta_1, \beta_2, \ldots, \beta_n$—regression coefficients;
$\in$—error.

In this context, Y represents the dependent variable, while X_1 through X_n denote the independent variables. The symbol β_0 indicates the intercept, β_1 through β_n are the regression coefficients, and $\in$ signifies an error. ANOVA tests were used to evaluate the statistical significance of the model.

To deepen the analysis, the general linear model (GLM) approach extends regression to handle multiple dependent variables at the same time. This method uncovers more complex relationships between digitalization indicators and AI integration [70].

Cluster analysis, utilizing Ward's method, grouped countries based on their levels of digitalization and AI adoption. This approach minimizes within-cluster variance while maximizing variance between clusters, using Euclidean distance as the similarity metric [71]. The merging cost function employed in Ward's algorithm is expressed as follows [72] (3):

$$\Delta(A,\ B) = \sum_{i\in A\cup B}\left|\left|\vec{x}_i - \vec{m}_{A\cup B}\right|\right|^2 - \sum_{i\in A}\left|\left|\vec{x}_i - \vec{m}_A\right|\right|^2 - \sum_{i\in B}\left|\left|\vec{x}_i - \vec{m}_B\right|\right|^2 = \frac{n_A n_B}{n_A + n_B}\,||\vec{m}_A - \vec{m}_B||^2 \tag{3}$$

$\vec{m}_j$—the center of cluster j;
n_j—number of points in cluster j;
Δ—merging cost of combining the clusters A and B;
i—cases.

AI attractiveness was not included as a separate variable in the statistical models but was indirectly captured through the share of enterprises engaged in e-commerce (ECOMM_PE). This indicator reflects the market engagement in e-commerce, which is commonly used as a proxy for sectoral attractiveness at the macroeconomic level. Regarding control variables, the analysis included one factor to account for structural differences across countries. EICTC acts as a proxy for digital labor capacity, controlling for differences in technical workforce availability, which can affect both AI adoption and e-commerce activity.

Furthermore, using cluster analysis complements the regression and GLMs by grouping countries with similar structural conditions, which helps reduce omitted-variable bias and improves the robustness of our interpretation. These statistical techniques together offer a detailed and nuanced framework for examining digitalization trends and the adoption of advanced technologies in European economies. They support hypothesis testing, identify structural patterns, and ultimately provide meaningful insights into how AI is transforming the e-commerce landscape.

4. Results

To investigate Hypothesis H1—specifically, that the use of AI in e-commerce positively affects both the proportion of businesses engaging in online sales and the total revenue generated through e-commerce—three main statistical methods were used: factor analysis, linear regression, and multivariate GLM. These methods offered a strong framework for analyzing the relationships among key variables and for evaluating the actual impact of artificial intelligence on digital commercial performance.

The factor analysis performed on the four variables—ECOMM_PT, ECOMM_PE, EICTC, and AIMS—offered valuable insights into the data's underlying structure and uncovered meaningful relationships among them. The correlation matrix showed significant associations, especially between the share of e-commerce revenue and the proportion of businesses that sell online. This result indicates a strong link between e-commerce presence and financial results, suggesting that companies actively engaged in digital commerce tend to generate substantial income through these channels (Table 2). AI adoption in marketing and sales also showed a moderate positive correlation with these variables, implying a potentially beneficial effect on e-commerce performance. Conversely, the proportion of ICT specialists (EICTC) demonstrated only weak correlations, indicating a more limited role in directly supporting e-commerce or AI adoption.

Table 2. Correlation matrix, KMO, and Bartlett's test.

		ECOMM_PT	ECOMM_PE	EICTC	AIMS
Correlation	ECOMM_PT	1.000	0.628	0.208	0.416
	ECOMM_PE	0.628	1.000	0.431	0.543
	EICTC	0.208	0.431	1.000	0.288
	AIMS	0.416	0.543	0.288	1.000

Table 2. *Cont.*

		ECOMM_PT	ECOMM_PE	EICTC	AIMS
Sig. (1-tailed)	ECOMM_PT		0.000	0.148	0.015
	ECOMM_PE	0.000		0.012	0.002
	EICTC	0.148	0.012		0.072
	AIMS	0.015	0.002	0.072	
Kaiser–Meyer–Olkin Measure of Sampling Adequacy.				0.684	
Bartlett's Test of Sphericity		Approx. Chi-Square		25.832	
		df		6	
		Sig.		0.000	

Source: analysis conducted using SPSS v.27.0 based on data collected from Eurostat [65–68].

The KMO measure confirmed that the dataset was suitable for factor analysis, and Bartlett's test showed that the variables were sufficiently interrelated to justify using this method.

Communalities helped evaluate how well each variable matched the extracted factor. ECOMM_PE emerged as the variable best explained within the structure. At the same time, EICTC showed a very low communality, suggesting that other external factors beyond those captured in this model may influence the presence of ICT specialists (Table 3).

Table 3. Communalities and factor matrix.

	Initial	Extraction	Factor1
ECOMM_PT	0.408	0.417	0.646
ECOMM_PE	0.549	0.903	0.950
EICTC	0.198	0.182	0.426
AIMS	0.309	0.365	0.604

Source: analysis conducted using SPSS v.27.0 based on data collected from Eurostat [65–68].

The total variance explained by the extracted factor showed that it accounted for almost half of the dataset's variability, highlighting a key dimension of the phenomenon studied (Table 4). Only one factor met the eigenvalue threshold (>1), representing a general dimension linked to both e-commerce performance and AI integration in business operations.

Table 4. Total variance explained.

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.291	57.268	57.268	1.868	46.691	46.691
2	0.814	20.343	77.611			
3	0.586	14.642	92.253			
4	0.310	7.747	100.000			

Source: analysis conducted using SPSS v.27.0 based on data collected from Eurostat [65–68].

This primary factor correlated most strongly with ECOMM_PE, moderately with ECOMM_PT and AIMS, and only weakly with EICTC. The findings support the idea that e-commerce performance and AI use form a unified construct that explains a large part of the observed variation. However, the weaker role of ICT specialists suggests that their presence alone does not drive digital transformation in e-commerce. This may reflect other reasons for hiring ICT professionals or the impact of unmeasured factors, such as digital infrastructure or firm-level strategies.

The study also used linear regression to quantify the relationship between the percentage of firms utilizing AI in marketing and sales (AIMS) and the percentage of firms involved in e-commerce sales (ECOMM_PE). The results confirmed a statistically significant and positive relationship. Businesses that incorporate AI into their commercial processes are more likely to engage in online trade. The model indicated that AI usage accounted for approximately 29.5% of the variation in the share of firms participating in e-commerce, suggesting a meaningful, though not complete, influence. The adjusted R-squared value was slightly lower, indicating that other variables probably contributed. Residual errors remained moderate, with no major prediction issues detected (Table 5).

Table 5. Linear regression model with ECOMM_PE as the dependent variable.

Model Summary						
Model		R	R Square		Adjusted R Square	Std. Error of the Estimate
1		0.543	0.295		0.267	7.34960
ANOVA						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	564.402	1	564.402	10.449	0.003
	Residual	1350.415	25	54.017		
	Total	1914.817	26			
Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	13.459	3.378		3.985	0.001
	AIMS	4.748	1.469	0.543	3.232	0.003
a. Dependent Variable: ECOMM_PE; b. Predictors: (Constant), AIMS						

Source: analysis conducted using SPSS v.27.0 based on data collected from Eurostat [65–68].

The ANOVA test confirms the statistical significance of the model, providing strong evidence that AI adoption has a real impact on increasing the number of firms engaged in e-commerce. The intercept indicates that even without AI usage in marketing, a small proportion of enterprises would still participate in online sales. Meanwhile, the regression coefficient shows that for every one-percentage-point increase in the use of AI in marketing and sales, the share of companies active in e-commerce is expected to grow by approximately 4.75%. This effect is statistically significant, reinforcing the idea that digitizing marketing processes through AI can help companies access the e-commerce landscape more effectively.

The linear regression model reveals a clear and positive relationship between using AI technologies for marketing or sales (AIMS) and the proportion of firms conducting sales through e-commerce (ECOMM_PE). The results are statistically significant, supporting the model's validity within the examined data and allowing for reasonable predictions.

A second regression model explores the relationship between the proportion of companies involved in e-commerce (ECOMM_PT) as the dependent variable and the percentage of those using AI technologies for marketing or sales (AIMS) as the independent variable.

The analysis shows a statistically significant, but weaker, connection compared to the earlier model. The correlation coefficient suggests a positive yet modest link, implying that businesses adopting AI in marketing and sales tend to experience increases in e-commerce revenue. However, this effect remains small (Table 6).

Table 6. Linear regression model with ECOMM_PT as the dependent variable.

Model Summary						
Model		R	R Square		Adjusted R Square	Std. Error of the Estimate
1		0.416	0.173		0.140	6.10171
ANOVA						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	194.782	1	194.782	5.232	0.031
	Residual	930.771	25	37.231		
	Total	1125.553	26			
Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	12.437	2.804		4.435	0.000
	AIMS	2.789	1.219	0.416	2.287	0.031
a. Dependent Variable: ECOMM_PT; b. Predictors: (Constant), AIMS						

Source: analysis conducted using SPSS v.27.0 based on data collected from Eurostat [65–68].

The model explains about 17.3% of the variance in e-commerce revenue. However, the adjusted R-squared value slightly lowers this explanatory power. This effect suggests that while AI influences online revenue, a significant portion of the variation is attributed to factors not accounted for in the model. The relatively high residual errors show substantial variability in the data, likely due to industry-specific differences, company size, or broader contextual factors.

The analysis of variance confirms once again the model's statistical significance, indicating that AI adoption indeed has a meaningful impact on e-commerce revenue. However, its effect on the number of firms involved in this sector is less pronounced. The regression coefficient supports this conclusion, suggesting that a one-percentage-point increase in AI usage is associated with an estimated 2.789% rise in e-commerce revenue. While statistically significant, this effect is smaller than the one observed for the growth of e-commerce participation.

The use of AI in marketing and sales boosts revenue growth in e-commerce; however, its overall impact remains limited, accounting for only a small portion of the total variation in revenue growth. Compared to its effect on the number of active online vendors, AI's influence on revenue generation appears to be weaker. This finding indicates that success in the digital market relies on other factors such as pricing strategies, digital infrastructure, and market demand. Therefore, while AI is a valuable tool for e-commerce growth, it is not the sole factor driving financial performance in this sector.

AI has a significant impact on e-commerce, as shown by a multivariate analysis (GLM) examining the relationship between sales, marketing AI use, and e-commerce performance. While their impact on overall e-commerce revenue is less pronounced, statistical results suggest that businesses utilizing AI are more likely to engage in online sales.

Descriptive statistics show that the average revenue from e-commerce is about 18.26%, while the typical share of businesses selling online is 23.37%. Both measures vary significantly across companies. Multivariate testing confirms that using AI significantly predicts both variables, as indicated by the Wilks' Lambda test with a significance level of 0.013. This result suggests that AI technologies have a moderate impact on the combined variation in e-commerce revenue and market adoption, accounting for approximately 30.4% of their shared variance (Table 7).

Table 7. Multivariate tests.

	Effect	Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power
Intercept	Pillai's Trace	0.484	11.251	2.000	24.000	0.000	0.484	22.501	0.984
	Wilks' Lambda	0.516	11.251	2.000	24.000	0.000	0.484	22.501	0.984
	Hotelling's Trace	0.938	11.251	2.000	24.000	0.000	0.484	22.501	0.984
	Roy's Largest Root	0.938	11.251	2.000	24.000	0.000	0.484	22.501	0.984
AIMS	Pillai's Trace	0.304	5.244	2.000	24.000	0.013	0.304	10.487	0.782
	Wilks' Lambda	0.696	5.244	2.000	24.000	0.013	0.304	10.487	0.782
	Hotelling's Trace	0.437	5.244	2.000	24.000	0.013	0.304	10.487	0.782
	Roy's Largest Root	0.437	5.244	2.000	24.000	0.013	0.304	10.487	0.782

a. Design: intercept + AIMS
b. Exact statistic
c. Computed using alpha = 0.05

Source: analysis conducted using SPSS v.27.0 based on data collected from Eurostat [65–68].

The univariate analysis offers a clearer view of AI's influence on each variable. AI accounts for about 17.3% of the variance in e-commerce revenue and nearly 30% of the variation in the number of firms selling online. This difference indicates that AI has a more significant role in encouraging firms to enter the e-commerce space than in directly increasing revenue (Table 8).

Table 8. Tests of between-subjects effects.

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power
Corrected Model	ECOMM_PT	194.782	1	194.782	5.232	0.031	0.173	5.232	0.594
	ECOMM_PE	564.402	1	564.402	10.449	0.003	0.295	10.449	0.874
Intercept	ECOMM_PT	732.328	1	732.328	19.670	0.000	0.440	19.670	0.989
	ECOMM_PE	857.641	1	857.641	15.877	0.001	0.388	15.877	0.969
AIMS	ECOMM_PT	194.782	1	194.782	5.232	0.031	0.173	5.232	0.594
	ECOMM_PE	564.402	1	564.402	10.449	0.003	0.295	10.449	0.874
Error	ECOMM_PT	930.771	25	37.231					
	ECOMM_PE	1350.415	25	54.017					

Table 8. *Cont.*

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power
Total	ECOMM_PT	10,129.194	27						
	ECOMM_PE	16,665.260	27						
Corrected Total	ECOMM_PT	1125.553	26						
	ECOMM_PE	1914.817	26						

a. R Squared = 0.173 (Adjusted R Squared = 0.140)
b. R Squared = 0.295 (Adjusted R Squared = 0.267)
c. Computed using alpha = 0.05

Source: analysis conducted using SPSS v.27.0 based on data collected from Eurostat [65–68].

This conclusion is further supported by the regression coefficients, which indicate that each additional increase in AI adoption is associated with a 2.79% rise in e-commerce revenue and a more notable 4.75% increase in the number of businesses engaged in online sales (Table 9).

Table 9. Parameter estimates.

Dependent Variable	Parameter	B	Std. Error	t	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power
ECOMM_PT	Intercept	12.437	2.804	4.435	0.000	0.440	4.435	0.989
	AIMS	2.789	1.219	2.287	0.031	0.173	2.287	0.594
ECOMM_PE	Intercept	13.459	3.378	3.985	0.001	0.388	3.985	0.969
	AIMS	4.748	1.469	3.232	0.003	0.295	3.232	0.874

Source: analysis conducted using SPSS v.27.0 based on data collected from Eurostat [65–68].

These findings suggest that while artificial intelligence facilitates the adoption of online sales, a company's financial success in this sector also depends on other key factors, including marketing strategies, digital infrastructure, and consumer behavior. The effect of AI on e-commerce is complex: on one hand, it boosts market participation by encouraging more companies to enter the space; on the other hand, its direct impact on revenue appears to be more limited, likely due to intense competition or broader economic conditions. The strong statistical power of the tests enhances the reliability of these conclusions, confirming that the results are not due to chance.

AI plays a vital role in transforming the e-commerce landscape; however, its implementation alone does not ensure automatic revenue growth. Instead, it helps facilitate market entry, with long-term financial success depending on a combination of strategic and economic factors.

Hypothesis H1 has been confirmed, showing that AI use in e-commerce positively affects both the proportion of businesses involved in online sales and sectoral revenue. However, the impact is more substantial on increasing firms' digital presence, while its effect on earnings is relatively limited. This finding suggests that financial success in e-commerce depends on other factors, such as pricing strategies, technological infrastructure, and market demand. In this context, AI serves as a helpful, yet not exclusive, tool for driving e-commerce growth.

To test Hypothesis H2, hierarchical clustering with Ward's method grouped European countries based on their levels of digitalization and adoption of advanced technologies.

This method offered a clear view of the relationship between AI usage, the share of firms involved in e-commerce, and revenue generated in the sector.

The cluster analysis shows how European economies group based on digitalization levels, highlighting the relationship between e-commerce revenue, the share of online-selling businesses, the number of ICT specialists, and AI use in marketing and sales. This approach not only highlights differences among countries but also reveals common patterns that enhance our understanding of digital transformation. Figure 2 and Appendix A Table A1 display the two resulting clusters.

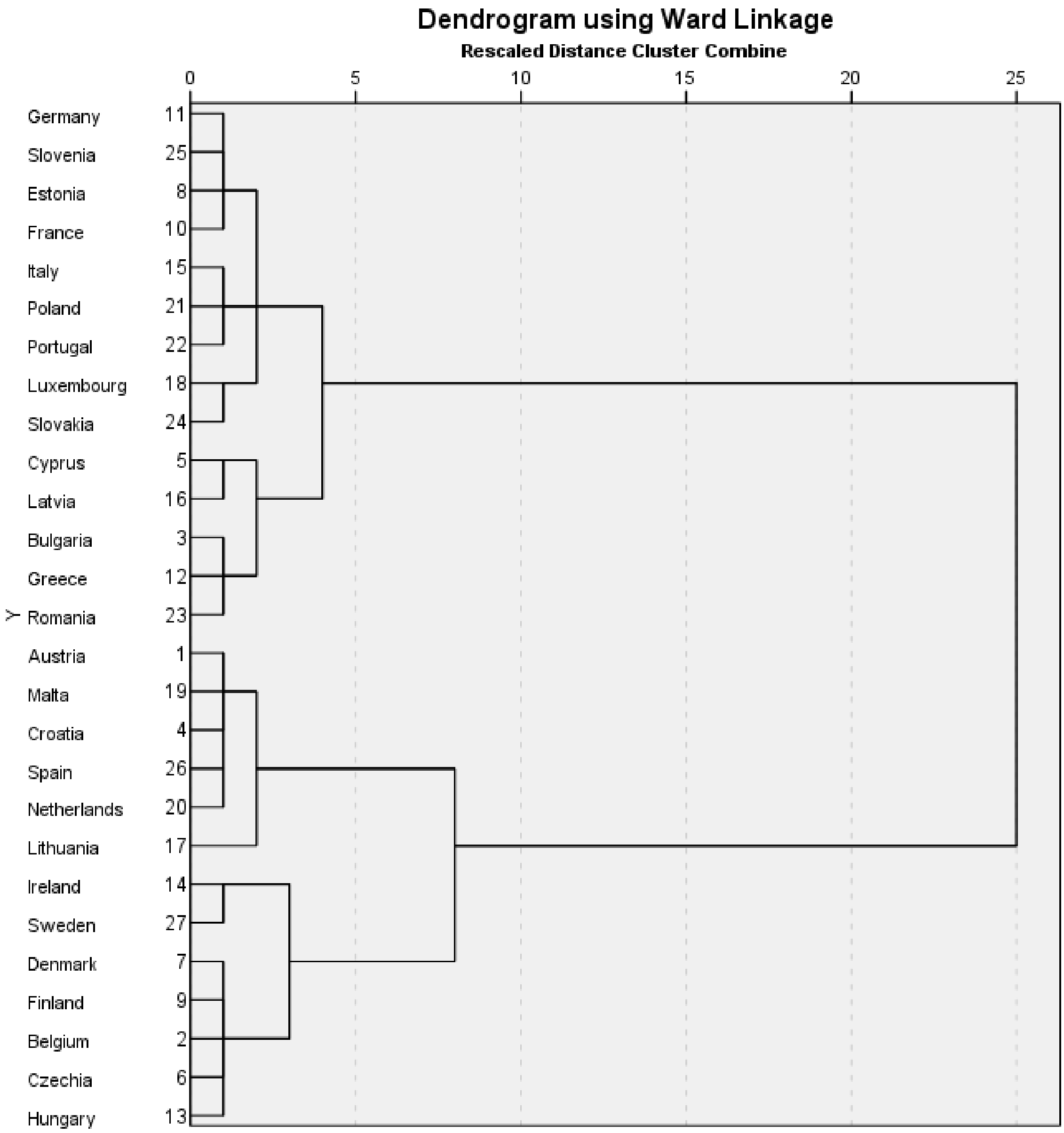

Figure 2. Dendrogram. Source: analysis conducted using SPSS v.27.0 based on data collected from Eurostat [65–68].

Cluster A, divided into two subgroups (A1 and A2), includes countries that, despite showing strong engagement in e-commerce, still fall behind the European average in adopting advanced technologies like artificial intelligence (AI). Subcluster A1—comprising countries such as Germany, Slovenia, and Luxembourg—stands out for its relatively high e-commerce turnover and number of online selling businesses, indicating a strong digital economy. However, their limited use of AI in marketing and sales points to untapped potential for technological innovation, despite broad e-commerce adoption. Subcluster A2—consisting of Cyprus, Bulgaria, and Greece—shows lower levels of e-commerce activity and advanced technology use, highlighting an urgent need for investments in digital infrastructure and ICT workforce development.

In contrast, Cluster B—also divided into two subgroups (B1 and B2)—includes countries that are not only leading in digitalization but also actively incorporate advanced technologies into their economies. Subcluster B1, which comprises Austria, Malta, and Ireland, is characterized by high percentages of online-selling businesses and ICT specialists, reflecting highly connected, innovation-driven economies. These countries also demonstrate significantly greater use of AI in marketing and sales compared to Cluster A, indicating a strong commitment to digital adoption and continuous innovation. Subcluster B2, which includes Denmark, Finland, and the Czech Republic, supports this trend with impressive e-commerce revenue and advanced AI applications, turning digitalization into a key competitive advantage.

The comparison between clusters reveals a distinct difference in their adoption of advanced technologies. Cluster B surpasses Cluster A in both AI usage and the number of ICT specialists, indicating that countries in this group have successfully created environments that are innovation- and digitalization-friendly. This progress is likely due to effective research and development policies, as well as a strong focus on education and skills development within the tech sector.

Hypothesis H2 has been confirmed, demonstrating that countries with higher use of AI in marketing and sales (AIMS) also have a greater proportion of enterprises engaged in e-commerce (ECOMM_PE) and higher e-commerce turnover. The cluster analysis revealed that countries in Cluster B—Austria, Malta, Ireland, Denmark, Finland, and the Czech Republic—are leading in digitalization, adopting advanced technologies and achieving outstanding e-commerce results. Conversely, countries in Cluster A—Germany, Slovenia, Luxembourg, Cyprus, Bulgaria, and Greece—have untapped potential, emphasizing the need for additional investment in digitalization and innovation. These findings provide a foundation for developing coordinated European strategies to promote an inclusive and competitive digital economy.

5. Discussion

In an economic landscape deeply influenced by digitalization, the use of artificial intelligence (AI) in e-commerce has shifted from being a competitive advantage to a strategic necessity. As consumer behavior becomes more sophisticated and expectations for seamless digital experiences increase, companies that successfully integrate AI technologies into their operations are better equipped to meet these evolving demands. The academic literature highlights AI's transformative potential in e-commerce by streamlining processes, personalizing products, and boosting customer engagement [23,28].

Building on this theoretical foundation, the current study examined two main hypotheses. The first hypothesis (H1) suggests that the percentage of businesses selling online and the overall industry revenue are positively affected by the use of AI in e-commerce. The second hypothesis (H2) indicates a link between the degree of digitalization and the adoption of these technologies, with countries that use AI more extensively in marketing and sales typically showing higher e-commerce activity and greater economic success.

Findings related to the first hypothesis emphasize the role of AI in helping companies build a digital presence. These results align with prior studies by Salah and Ayyash [31] and Branda et al. [3], which showed that implementing AI in marketing results in a measurable boost in firms' engagement with digital sales channels. Likewise, Verma et al. [4] observed that AI-driven personalization and segmentation strategies significantly increase e-commerce conversion rates.

Furthermore, the ability of AI to enhance targeting, automate communication, and analyze consumer data in real time is supported by the findings of Davenport and Ronanki [30] and Kitchens et al. [27], who noted that data-driven marketing decisions driven by AI lead to improved customer acquisition and retention. Consequently, AI plays a critical role not only in attracting customers but also in nurturing long-term relationships—developments that, in theory, should lead to improved financial performance [73,74]. Our analysis agrees with these findings, confirming that countries with a higher percentage of firms using AI in marketing (AIMS) also exhibit greater participation in e-commerce (ECOMM_PE).

Our results also show that while AI adoption promotes firms' involvement in online commerce, its direct effect on turnover (ECOMM_PT) remains modest. This detail is supported by the work of Li et al. [28] and Madanchian [34], who emphasize that AI integration must be paired with a broader strategic alignment—encompassing infrastructure, logistics, and pricing—for revenue gains to be fully realized. Therefore, our findings underscore that AI acts as an enabler rather than the sole driver of e-commerce success.

This observation is further supported by Zong et al. [7] and Bawack et al. [35], who argue that the impact of AI technologies heavily depends on organizational readiness, data culture, and leadership adaptability. Without a supportive environment, the full potential of AI remains untapped. Therefore, our study confirms previous conclusions that AI integration should be part of a broader digital transformation framework [22,35].

The first hypothesis is thus confirmed, but with a necessary clarification: AI seems to contribute more to increasing the number of firms involved in e-commerce than to maximizing their revenues. This indicates that AI plays a key role in democratizing access to digital markets, especially for SMEs [12], while financial results continue to depend on a complex interplay of related factors [5].

Turning to the second hypothesis, the relationship between AI usage in marketing and national digitalization levels was examined through a cross-country comparison. The findings confirm previous research indicating that countries with more advanced digital infrastructures and consistent policy frameworks have higher levels of e-commerce activity and AI integration [8,11,42,75]. The results align with those of Ozturk [14] and Rahayu and Day [10], who have demonstrated that national investments in ICT skills and infrastructure significantly impact the effectiveness of technology and business outcomes.

Furthermore, our identification of two distinct country clusters—those with high AI adoption and e-commerce performance versus those with lagging digital development—mirrors the typologies described by Bhatia and Thakur [46] and OECD [11]. These studies emphasized that digital readiness and institutional support foster the spread of innovation and improve performance.

Consequently, Hypothesis H2 is validated: countries with higher integration of AI tools in marketing and sales report better e-commerce results, confirming the utility of AI as a proxy for digital maturity. Our study, therefore, strengthens the empirical foundation for previous claims about the strategic role of AI in driving economic competitiveness through digital channels [1,2,42].

In conclusion, both hypotheses explored in this study were validated. Our contribution expands the current literature by providing a macro-level comparative perspective that demonstrates how AI promotes e-commerce participation, despite its limited direct impact on revenue. These findings align with recent research by Xu and Ruan [29] and Loureiro et al. [55], which highlight that technology-driven engagement does not necessarily lead to financial success.

Ultimately, our findings reinforce the growing consensus that the real value of AI lies in its integration into comprehensive digital strategies, supported by leadership, infrastructure, and a culture of innovation. As artificial intelligence continues to advance, its success in improving e-commerce results will rely not only on technical implementation but also on broader organizational and systemic preparedness [5,22,33].

5.1. Theoretical Implications

Our study significantly advances understanding of how AI technologies influence e-commerce development across various European settings. Through comparative analysis, this research offers a critical view of the idea that AI's impact follows uniform or universally applicable patterns. Instead, our data indicate that the dynamics of AI adoption and successful implementation rely on a complex interplay of structural and cultural factors unique to each country. This finding highlights the need to reevaluate the relationship between technology and digital economic growth within a theoretical framework that prioritizes local contexts and transcends simplistic, one-size-fits-all models. Consequently, the paper suggests reevaluating theories on innovation and technology diffusion by highlighting how local ecosystems interact with emerging technologies. Furthermore, the results show a dynamic rather than linear connection between AI integration and e-commerce performance, implying that technological gains are most likely when organizational changes, digital skills, and a culture of experimentation accompany innovation.

5.2. Practical Implications

Beyond theoretical contributions, our research conclusions offer valuable benchmarks for decision-makers, entrepreneurs, and professionals in the field of electronic commerce. The integration of AI in e-commerce should not be seen as a single goal, but rather as part of a comprehensive digital strategy tailored to national and sector-specific needs. Countries that have achieved the best results in AI-powered e-commerce performance are those that have successfully aligned technological investments with clear public policies, strong digital infrastructure, and active partnerships between the private and academic sectors. This emphasizes the importance of a systemic approach that goes beyond occasional AI implementations to transform the entire digital commerce value chain. Additionally, organizations in countries at the early stages of digitalization can learn from identified best practice models, adapting proven solutions to local realities. Specifically, we highlight the importance of developing digital skills among staff, investing in data infrastructure, and encouraging greater openness to innovation, including through international collaborations.

5.3. Limitations and Future Research Directions

Like any scientific effort, this research recognizes certain limitations that guide promising directions for future studies. First, the comparative nature of the study required combining datasets from national and European sources, which may introduce inconsistencies in quality and timing. Additionally, the analysis primarily focused on quantitative indicators, which limited a comprehensive understanding of the organizational and cultural factors that influence AI's impact on e-commerce performance. A qualitative extension using case studies or interviews with relevant participants could effectively enhance the overview provided here. Moreover, focusing solely on the European context allows for global-scale comparisons that can test the validity of the conclusions in a broader setting. Finally, the fast pace of AI technology development calls for continuous research updates, pointing to the potential for longitudinal studies that can track implementation processes and their medium- and long-term effects.

6. Conclusions

This study aimed to examine how AI technologies influence the performance and structure of the European e-commerce industry. Two main objectives guided the research: first, to assess how AI use in marketing and sales impacts e-commerce performance; and second, to analyze how digital maturity at the national level affects this relationship across European countries.

To achieve these objectives, we used a quantitative, macro-level approach utilizing data from Eurostat. The analysis employed four statistical techniques—factor analysis, linear regression, multivariate general linear modeling, and hierarchical cluster analysis. These methods helped explore both direct relationships and systemic patterns among five key indicators: enterprise engagement in e-commerce, online sales turnover, AI integration in marketing, the presence of ICT specialists, and digital infrastructure.

The results confirmed both research hypotheses. First, we found that AI adoption in marketing and sales is strongly connected to the percentage of firms involved in e-commerce, although its impact on revenue is more limited. This finding indicates that AI enables firms to enter digital markets, but it does not guarantee immediate financial gains, which depend on other factors such as digital infrastructure, pricing strategies, and market demand. Second, the comparative analysis identified two distinct groups of countries based on digital maturity and AI integration, highlighting that systemic readiness—including digital skills, policy support, and organizational culture—is essential for effectively leveraging AI.

These findings underscore the significance of context in comprehending the economic implications of AI. While the technology itself provides valuable capabilities, its transformative potential depends on how it is integrated into broader digital strategies. The study's main contribution is in connecting theoretical insights with empirical evidence across different countries, thus avoiding both excessive optimism and oversimplified conclusions. Instead, the paper offers a nuanced, evidence-based perspective on AI's role in e-commerce growth within the European Union.

On a practical level, the conclusions guide policymakers, business leaders, and researchers. Instead of concentrating solely on acquiring technology, stakeholders should focus on developing digital capabilities, aligning innovation policies, and fostering adaptive organizational environments. Only through an integrated approach can the full potential of AI in e-commerce be unlocked.

Future research should build on these findings by expanding the analysis to global markets, incorporating qualitative case studies to understand micro-level dynamics, and employing longitudinal designs to track the development of AI's impact. As AI continues to evolve, it is crucial to study not just what it enables but also how, under what conditions, and to what extent it influences society and the economy.

AI's role in e-commerce should be viewed not just as a technical task but as part of a complex socio-technical system influenced by digital infrastructure, institutional backing, and strategic objectives. This broader perspective offers a more realistic and practical approach to understanding and managing the ongoing digital transformation.

Author Contributions: Conceptualization, C.G.B., D.S., L.P., N.M.S., C.P., R.C.M. and E.M.; methodology, C.G.B., D.S., L.P., N.M.S., C.P., R.C.M. and E.M.; software, C.G.B.; validation, C.G.B., D.S., L.P., N.M.S., C.P., R.C.M. and E.M.; formal analysis, C.G.B., D.S., L.P., N.M.S., C.P., R.C.M. and E.M.; investigation, C.G.B., D.S., L.P., N.M.S., C.P., R.C.M. and E.M.; resources, C.G.B., D.S., L.P., N.M.S., C.P., R.C.M. and E.M.; data curation, C.G.B.; writing—original draft preparation, C.G.B., D.S., L.P., N.M.S., C.P., R.C.M. and E.M.; writing—review and editing, C.G.B., D.S., L.P., N.M.S., C.P., R.C.M. and E.M.; visualization, C.P., R.C.M. and E.M.; supervision, D.S., L.P. and N.M.S.; project

administration, C.G.B. All authors have contributed equally to this paper. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data is contained within the article. The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare that they have no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ECOMM_PT	Enterprises' total turnover from e-commerce sales
ECOMM_PE	Enterprises with e-commerce sales
EICTC	Employed ICT specialists
AIMS	Enterprises use AI technologies for marketing or sales

Appendix A

Table A1. Cluster data.

	ECOMM_PT	ECOMM_PE	EICTS	AIMS
Germany	17.71	20.91	4.3	2.07
Slovenia	17.15	19.95	4.2	2.43
Estonia	15.59	22.47	2.4	1.68
France	11.49	19.66	4.7	1.02
Italy	17.34	15.17	4.9	1.67
Poland	17.25	16.62	4.3	1.45
Portugal	18.99	12.56	4.5	1.95
Luxembourg	24.27	16.67	4.7	2.23
Slovakia	21.55	16.94	3.8	1.88
Subcluster A1 means	17.93	17.88	4.20	1.82
Cyprus	12.58	13.73	4.9	1.66
Latvia	10.22	18.01	8.0	1.24
Bulgaria	6.32	10.01	4.3	1.15
Greece	7.07	13.88	4.1	0.87
Romania	11.55	12.85	2.6	0.99
Subcluster A2 means	9.55	13.70	4.78	1.18
Cluster A means	14.58	16.21	4.43	1.56
EU means	18.26	23.37	5.08	2.09
Austria	14.20	27.26	5.4	3.10
Malta	12.98	23.60	6.9	4.04
Croatia	15.28	31.50	5.9	1.73
Spain	19.35	30.93	7.6	2.23
the Netherlands	18.99	29.32	5.3	3.97
Lithuania	15.54	30.53	4.2	1.05
Ireland	28.39	39.52	4.4	2.79
Sweden	25.56	41.73	8.7	2.92

Table A1. *Cont.*

	ECOMM_PT	ECOMM_PE	EICTS	AIMS
Subcluster B1 means	18.79	31.80	6.05	2.73
Denmark	28.64	31.41	6.2	3.70
Finland	24.93	33.40	4.4	3.98
Belgium	26.56	31.58	4.3	2.14
Czechia	30.49	26.31	6.7	1.24
Hungary	23.06	24.56	5.4	1.20
Subcluster B2 means	26.74	29.45	5.40	2.45
Cluster B means	22.19	30.79	5.77	2.61
EU means	18.26	23.37	5.08	2.09

Source: analysis conducted using SPSS v.27.0 based on data collected from Eurostat [65–68].

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